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Article (Accepted Version)

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April 21, 2017

Abstract

Alert programs are central to strategies to reduce pollution exposure and manage its impact. To be effective alerts have to change behavior, but evidence that they do that is sparse. Indeed the majority of published studies fail to find a significant impact of alerts on the outcome behavior that they study. Alerts particularly seek to influence energetic cardio-vascular outdoor pursuits. This study is the first to use administrative data to show that they are effective in reducing participation in such a pursuit (namely cycle use in Sydney, Australia), and to our knowledge the first to show that they are effective in changing any behavior in a non-US setting. We are careful to disentangle possible reactions to realised air quality from the 'pure', causal effect of the issuance of an alert. Our results suggest that when an air quality alert is issued, the amount of cycling is reduced by 14 to 35%, which is a substantial behavioral response. The results are robust to the inclusion of a battery of controls in various combinations, alternative estimation methods and non-linear specifications. We develop various sub-sample results, and also find evidence of alert fatigue.

Keywords: Information-based regulation; averting behavior; urban air quality; health impacts of air pollution.

*Heyes is also a part-time Professor of Economics at the University of Sussex. We are grateful to Pierre Brochu, Maya Papineau, Matthew Neidell, Brandon Schaufele, Joel Bruneau, participants at the 2014 Meeting of the CREE and two referees from this journal for very constructive comments. Heyes and Rivers both hold Canada Research Chairs and acknowledge the financial support of the Social Science and Humanities Research Council Canada Research Chairs (CRC) program. Errors are ours.

1 Introduction

Managing the impact of pollution exposure - particularly in big cities - is a key policy priority in many countries. In addition to efforts to reduce pollution levels directly, policy-makers put increasing faith in information-based programs that enable individuals to engage in avoidance behavior to alleviate the negative effects of pollution.

A prominent example of this is the air quality 'alert' schemes that are now in operation in many cities across North America and elsewhere.[1] When air quality is forecast to be poor - fall below some established threshold - an alert or advisory is issued and people are encouraged to change behavior in order to reduce exposure. Typically alerts focus in particular on encouraging people to avoid strenuous outdoor activities.[2]

The evidence that alerts work, however, is thin. Our paper is the first to use administrative data to link air quality alerts to the avoidance of a strenuous outdoor activity. In particular, fine-grained administrative bicycle-count data from the cycle path network of Sydney, Australia allows us to investigate the impact of air quality alerts on cycling behavior in that city. To the best of our knowledge, there are only two existing papers that link alerts to directly-observed avoidance behavior using administrative data. One is Graff Zivin and Neidell (2009) who use turnstile data to show that alerts impact attendance at two popular outdoor venues in Los Angeles (Los Angeles Zoo and The Griffith Observatory) especially amongst those with children. The other is Noonan (2014) who uses data from a small-scale survey of people passing two park benches in a 35 day period in Piedmont Park in Atlanta. He gets mixed results, finding no impact of alerts on aggregate use but evidence consistent with reduced use by older people and joggers.

We estimate the causal effect of air quality alerts on cycling behavior using a regression-based approach that relates daily cycling counts at each cycling counter on the Sydney bicycle network with a dummy variable indicating whether an air quality alert was in place. Recognizing that cyclists may decide whether or not to cycle based on the actual pollution level in addition to whether an alert is in place, we also include covariates to control for actual (concurrent) level of air quality (as well as other determinants of cycling behavior). However, this raises a concern, since air quality is potentially endogenous in our setting.

[1]For two examples amongst many, Toronto started an alert program in 2005, Hong Kong in 2013.

[2]Avoiding such activity is crucial in reducing the health risk to an individual of poor air quality. Carlisle and Sharp (2001) and Atkinson (1997) are among many studies that link exercising in polluted air to a variety of elevated health risks.

In fact, estimating the effect of air quality alerts on individuals' behavior is challenging for at least three reasons. First, because of variation in pollution across regions, assigning pollution and weather variables to individuals based on individual and monitor locations could lead to measurement error. Second omitted variable bias could arise due to confounding environmental factors. Third, the level of ambient pollution may be endogenous if individuals shift their outdoor activities toward emission-producing substitute activities (for example the presence of an air quality alert may induce some cyclists to drive). To accommodate this, we instrument for 'air quality' using bushfire activity.

It is important to clarify that our focus in the paper is on estimating the impact of air quality alerts on cycling behavior. Air quality alerts are established the day prior to the alert being issued (based on the *forecast* air quality on the day of the alert), are not revised after being set (to correct for forecast errors), and are city-wide. These conditions ensure that there is no measurement error or endogeneity directly associated with our main variable - the dummy variable for alerts. However, alerts are correlated with actual air quality, which is potentially endogenous, and which can also affect cycling behavior. We show that neglecting to address endogeneity in the air quality variable will lead to bias in our estimate of the effect of alerts on cycling behavior, and thus we use bushfires that occur throughout neighboring regions of Australia as an instrument for air quality in Sydney.

Three characteristics of bushfire activity point to it being a good instrument in this context. First, bushfires have a significant negative influence on air quality in Sydney. Smoke from bushfires consists of carbon dioxide, carbon monoxide, fine particulate matter, and oxides of nitrogen and can also increase ozone concentrations in the presence of sunlight. Because of hot dry conditions, particles from bushfires can be transported several thousand kilometers, and bushfire smoke from distant fires regularly impacts the air quality in the city (Confalonieri et al. (2007)). Second, the only channel through which bushfires can sensibly be expected to affect cycling behavior is through their impact on air quality. Third, the timing of bushfires is quasi-random. Although periods of hot and dry weather may create preconditions for fires, their occurrence cannot be perfectly timed.

Bushfire activity is introduced in combination with distance from city and size of fire, though results across the specifications prove similar. The reduction implied in cycle use in response to an alert is not just statistically significant but substantial in size - around 14% under OLS estimation and 35% under the preferred IV specification. We also explore the *dynamics* of response, finding evidence consistent with 'alert fatigue'. More concretely, when alerts are issued for two successive days, the second day response is much smaller (2% in the preferred IV specification) and no longer statistically significant, albeit in a much smaller sample.

The results presented prove robust in sign - and fairly robust in magnitude - to inclusion of alternative combinations of controls for weather, temporal factors, etc.. We recognize the risk of omitted variable bias, and estimates from a 'stripped down' version of the model excluding all pollution and weather controls point to a statistically significant 30% fall in cycle use in response to a single-day alert, suggesting the strength of our approach in controlling for potential environmental confounders. We also allow for the possibility of nonlinear effects of concurrent air quality on demand for cycling which, and in that case we find that air quality alerts cause a 15% and 26% reduction in cycling under OLS and IV estimation, respectively.

In addition to our main results, we also use the data to determine whether the response is greater for leisure or commuting cyclists. We conduct this analysis in two ways. First, we divide the data into weekdays and weekends, and find that the cyclists respond more to an air quality alert on weekends than weekdays (49% versus 30% in the preferred IV specification). Second, we categorize the cycle-counter locations according to two criteria - one a measure of the relative density of use of a particular route across days of the week (weekdays versus weekends), the other the "strength" of the peak in usage of a particular route during normal travel-to-work windows on an average weekday. Each criteria are designed to disentangle commuting from non-commuter traffic (counters provide a count of the number of bicycle passing - no information on the purpose of the trip). While neither of these proxies are perfect, they both suggest a stronger response to air quality alerts of leisure cyclists relative to commuter cyclists.

The layout of the rest of the paper is as follows. The next section summarizes the pertinent research from a number of streams of research in air quality, behavior and the impact of alerts. Section 3 describes data sources. Section 4 lays out the challenges of estimating avoidance behavior and describes our empirical strategy, with results contained in Section 5. Section 6 concludes.

2 Existing research

Air quality alerts are one of a number of information-based or so-called 'third wave' instruments that have become increasingly popular amongst environmental regulators in recent years. There are two main kinds of air quality alerts: (1) alerts with an objective of reducing exposure by giving people the information they need to allow them to engage in appropriate avoidance behavior - in particular to avoid outdoor cardiovascular activities when air quality is poor, and (2) alerts with an objective of reducing pollution by encouraging voluntary to use public transportation. These presumably induce different behavioral impacts, partly by design.

Evidence of the effectiveness of such programs is important for at least two reasons: (a) they are an important and increasingly popular instrument amongst health and environmental protection agencies and, (b) as noted by Neidell (2004), failing to take proper account of individual avoidance effort (whether or not stimulated by alerts) will bias downwards estimates of the health risks associated with pollution.

Three strands of literature provide relevant context for our analysis. First, some studies use *direct* measures of avoidance behavior by comparing participation in activities on days with and without alerts - this is the strand to which we seek to add here. Second, some studies infer something about avoidance behavior *indirectly* by assessing the relationship between air quality and health outcomes (prevalence of asthma, hospital admissions for cardiovascular and respiratory problems) in settings with and without alert programs in place. Third - given that our focus is on cycling - some studies relate how alerts impact transport choice, in particular driving behavior. We summarize key results from each of these strands of the literature in the following sections.

2.1 Alerts and direct measures of avoidance behavior

To quantify direct avoidance behavior previous studies use either survey data or outdoor attendance data.

Sexton (2011) uses the American Time Use Survey (ATUS) data to show that individuals avoid exposure to pollution by reducing time spent on vigorous outdoor activities by, on average, 18 minutes on alert days. Bresnahan et al. (1997); Mansfield et al. (2006); Wen et al. (2009) also use survey data.

Graff Zivin and Neidell (2009) use turnstile data on attendance at Los Angeles Zoo and Griffith Park Observatory as a measure of outdoor activity to examine how individuals adjust their time spent outdoors in response to a smog alert. They find that alerts reduce attendance at the zoo and observatory by 15 and 5 percent, respectively. However, if alerts are issued for two consecutive days, there is no statistically significant reduction on the second day.[3] Noonan (2014) investigates the change in the usage pattern of Piedmont Park in Atlanta in response to smog

[3] In an earlier version Neidell (2006) found no statistically significant reduction on attendance at Los Angeles County Arboretum.

alerts. He counts people passing two benches in the park on 35 days in the summer of 2005 and composition of groups. Of the 35 days 7 were subject to alerts. His findings show that aggregate park usage did not change on days with alerts compared to days without alerts but evidence is consistent with a fall in usage by the elderly and joggers.[4]

To the best of our knowledge, our study is the first to use administrative data on a strenuous cardiovascular activity to directly quantify avoidance behavior.

It is important to note that the existence of avoidance behavior by a physically active individual can play a crucial role in reducing the health risk associated with air pollution. In particular, previous studies such as Carlisle and Sharp (2001) and Atkinson (1997) find that exercising in poor air quality can increase health risks. The cardiovascular and respiratory effects of air pollution are amplified by exercising since exercisers inhale more pollutants. Cakmak et al. (2011) use the Canadian Health Measure Survey (CHMS)[5] data for 5,000 individuals aged 7 to 69 years to investigate the effect of air pollution on cardiovascular function of exercisers. Their results show that a 17 *ppb* increase in ozone is associated with a 1.5 percent reduction in aerobic fitness score.[6] In addition, Marr and Ely (2010) gather seven marathon race results to show that 10 increases in the level of PM10 will reduce the performance of female marathon runners by 1.4 percent. Of course we cannot precisely assess the health impact of reduced engagement in cycling without knowing to what alternative activities the cyclists turn, and the location of those activities, which is beyond the scope of this study.

2.2 Alerts and health outcomes

Since reducing damage to human health is the primary objective of clean air regulations, it is interesting to quantify the impact of air quality alerts by exploring the effect of alerts on health outcomes.

[4]Noonan (2014) uses regression discontinuity methods and works with *proportions* of users drawn from different categories so at times significance is less-straightforward to infer. His own summary is that: "(O)verall, smog alerts do not appear to significantly affect the aggregate park usage, even by sensitive subgroups, except the elderly. Individual groups of passers-by, on the other hand do appear affected by smog alerts - exercisers and elderly compose less of park users" (page 16). Noonan (2011) also uses data from the ATUS time-use diaries aggregated across a set of US cities to assess the impact of alerts on the probability of adult participation in evening sports but gets insignificant results.

[5]Starting in 2007, the Canadian Health Measures Survey (CHMS) has been gathering relevant information about Canadians' health by collecting main physical measurements such as blood pressure, height, weight and physical fitness.

[6]Aerobic fitness score computes the volume of oxygen that each individual needs to burn during peak exercise.

Neidell (2004) estimates the effect of ozone pollution on hospitalizations of children for asthma in California. He estimates that the decline in pollution levels from 1992 to 1998 reduced hospital admissions by between 5 and 14%. Moreover, he estimates that smog *alerts* reduce the asthma rate among children aged 6 to 12 years by 1%, providing indirect evidence of behavioral response to alerts. In another study the same author investigates the relationship between ozone levels and asthma hospitalizations in Southern California using a regression discontinuity approach (Neidell (2009)). He estimates that ozone alerts reduce asthma hospital admissions by a statistically significant 16% among those aged 5 to 19. In contrast Ward (2015) applies similar methods to a data-set from Ontario, Canada and finds no significant effect of alerts across most age groups. The exception is a significant but small impact that she finds for those aged over 65.[7]

2.3 Alerts and transport choice

There is a small literature on alerts impacting driving behavior and public transit usage, from contexts in which the stated goal and messaging associated with the alert program is to reduce pollution emissions (rather than pollution exposure).

Cummings and Walker (2000) develop a model to forecast aggregate daily traffic volumes in Atlanta so that they can compare the forecast volume of traffic with the observed volume on days with an ozone alert. They find no significant effect of alerts on traffic. Henry and Gordon (2003) use data from a telephone survey to analyze individuals' behavioral responses to smog alert program in Atlanta. Their regression results show that there is no significant effect of alerts on number of car trips or mileage driven by non-government employees.

Welch et al. (2005) use hourly turnstile counts from the Chicago Transit Association to evaluate the impact of alerts on public transit ridership in Chicago from 2002 to 2003. They were unable to find any significant impact of alerts on aggregate ridership, though the hourly pattern of ridership at both the morning and evening peak were pushed later.

Cutter and Neidell (2009) investigate how individuals in the San Francisco Bay Area change their transportation choice in response to pollution advisories.[8] They show that while advisories reduce the total volume of daily vehicle traffic by a

[7] However the threshold for issuing an alert is much higher in California (200 ppb) than Ontario (50 ppb). This can be expected to impact the personal cost-benefit of changing behavior in important ways.

[8] The Bay Area Air Quality Management District (BAAQMD) is required to issue an alert on days when the ground level of ozone is predicted to exceed National Ambient Air Quality Standards (NAAQS).

statistically significant 3 - 3.5%, they do not significantly change demand for public transportation (i.e., Bay Area Rapid Transit (BART)).

Tribby et al. (2013) use daily vehicle traffic data over a 10 year period in Salt Lake and Davis counties to investigate the effectiveness of particulate matter and ozone alerts, arriving at mixed results. They show that in response to alerts, car traffic in the city center falls by a statistically significant 2.1%, but traffic *increases* by 5.8% in areas closer to the edge of the metropolitan area.

3 Data

The study requires data on cycling behavior, air quality, air quality alerts, and a variety of potential control variables. These are assembled from a number of administrative sources all expected to be of high quality.

3.1 Cycling

Cycling in Sydney is popular, both as a means for getting to and from work, and as a leisure pursuit.

The city contains an extensive set of cycle-paths. The regional location of routes are categorized by sector: downtown, inner-north, inner-west, north, northwest, west central and south. Shown in Figure 1, within the city of Sydney there are 11 regional cycling routes.

The New South Wales (NSW) Department of Roads and Maritime Services operates a network of electronic path-side devices that record the number of cyclists passing at 31 points across different cycle-paths in the city (see Figure 2). We obtain the daily count of cycle movements from May 2008 to September 2013 for each of these counters, as well as hourly breakdowns.

The average length of each cycle path in the city is 6 km. Many of the routes are regarded locally as 'commuter' routes - primarily used for the purposes of getting to and from work. Others - such as that running from Sydney Park to Centennial Park - are more intensively used for leisure. Later in the paper we investigate the effect of alerts on the two different categorizations of routes.

Focusing on cycle movements as a measure of outdoor activity has several advantages. First, cycling is a widespread, energetic, cardiovascular activity that takes place outdoors. As such it is *precisely* the sort of behavior that those implementing alert schemes seek most-particularly to influence. Second, it allows the use of administrative rather than survey-derived data and therefore not subject to the vagaries of memory lapse or misrepresentation inherent in (for example) diary-based approaches. Third, the cycling data are available for an extended period (more than five years) which straddles significant variations in pollutant levels and alerts. Fourth, the counters provide reliable data across a range of different *types* of routes and for weekdays and weekends which allows for some interesting analysis of sub-samples.

Table 2 presents summary data on cycle counts and other variables. Between May 2008 and September 2013 the average number of bicycles passing each counter daily was about 354, but with a lot of variation across days and across counters. The system is about 20% more heavily used on weekdays than on weekend-days (an average count of 373 per weekday compared to 305 on a weekend day), though again this pattern varies a lot between counters.

Counters are excluded if they count fewer than 10 cyclists per day on average, which caused us to drop 5 of the 31 counters. There were 16 days from May 2008 to September 2013 in which all counters did not record properly (more correctly the transmission of data from the remote counters to the central database did not work due to technical problems, so all counters recorded zero) and those dates were dropped. Moreover, we drop those counters on specific days that are associated with missing values. After cleaning the data to remove those dates associated with missing values for explanatory variables - none of which would we have reason to think could be correlated with air quality - there remains an unbalanced panel of observations from 26 counters over 1831 days.

3.2 Pollution

Data on ambient concentrations of various airborne pollutants, air quality index (AQI) and air quality alerts are obtained from the responsible government body in the state of New South Wales, the NSW Office of Environment and Heritage (OEH). AQI is a common composite measure of air quality, and in our main model specifications, we control for the ambient pollution level using this variable.

There are 21 air quality monitoring stations around the Sydney region, 14 of which were operational throughout our study period. For each cycle counter we identified the closest station by comparison of GPS coordinates and by this means ended up using data from 6 air quality monitors.

The National Environmental Protection Council (NEPC) is responsible for regulating air quality in Australia. National standards for six major pollutants (namely ozone (O_3), carbon monoxide (CO), sulfur dioxide (SO_2), nitrogen dioxide (NO_2), lead and air particles ($PM_{2.5}$ and PM_{10})) are set by legislation, which also defines the methods by which these pollutants are measured and recorded. In NSW the OEH is tasked with surveillance. Each monitoring station collects hourly measurements of air pollutant concentrations which are used to construct daily and hourly AQI measures for each site and region. OEH reports daily and hourly AQI on its website and the daily measure is reported in local media (for summary data see Table 2.)

The AQI takes a value between 0 and 500 and in NSW is categorized into six levels: Very Good AQI = 0 - 33; Good AQI = 34 - 66; Fair AQI = 67 - 99; Poor AQI = 100 - 149; Very Poor AQI = 150 - 199; Hazardous AQI > 200.

Beyond the hourly and daily values of AQI, each day at 4 pm the OEH issues an AQI forecast for the next day. If any of the three most populous regions within Sydney (Eastern, North Western and South Western divisions) are forecast to have AQI above 100 the following day a health alert is issued by the NSW Office of Health for the whole city at the same time as the forecast. Although AQI is announced hourly, an air quality alert is announced more prominently on the OEH web pages (http://www.environment.nsw.gov.au), through twitter, e-mail and SMS notifications, and it is widely-reported in the media.

The process of forecasting air quality is informed by several types of data for different sources. These include, (1) the Air Quality Index (AQI) value for the previous 24 hours throughout the city, (2) the Bureau of Meteorology (BOM) forecast of weather conditions including wind speed, wind direction, rainfall, temperature, temperature inversion and cloud cover, (3) Rural Fire Service (RFS) to assess emission sources from bushfires when their presence is likely to cause elevated particle levels for the next day.

It is worthwhile mentioning that while the air quality index is updated every hour on the OEH webpage to reflect current observations of air quality, the alert status is not revised once it has been announced and is reported much more widely. Cyclists may select cycling behavior based on either or both of these inputs. For example, some cyclists may choose whether or not to cycle based only on the status of the alert. Others may check the OEH website prior to cycling, or avoid cycling if the sky appears smoky, as on a polluted day. Therefore we aim to control for both of these variables (the alert status as well as the actual air quality) in estimating cycling behavior.

In the event of alert the OEH also makes a statement about the particular pollutant which was primarily responsible for the alert being triggered. In fact, in our period of study 96% of air quality alerts were triggered by ozone.[9] Particularly,

[9]For a total of 1831 days, alerts are issued for 25 days and it is indicated that 24 of these are

as indicated by NSW EPA 2012, the ambient concentrations of CO, NO_2, and SO_2, are generally below the NEPM standards whereas the ground level of O_3 in urban areas and the concentrations of PM_{10} and $PM_{2.5}$ in urban and rural NSW often exceed the standards. Alerts on two consecutive days are unusual, occurring on only 7 occasions in our 1831 day study period.

3.3 Weather

In a study of this sort, it is important to control for potential confounding impacts of weather variables. Not only do weather conditions have an important influence on ambient pollution levels, such as ground level ozone, but can also be expected to have a direct effect on cycling behavior.

We seek to control for daily measures of both average and maximum daytime air temperature, precipitation, relative humidity, number of hours of bright sun between sunrise and sunset, total solar exposure and wind speed as weather variables in most of our regressions.

The weather data is obtained from the Australian Bureau of Meteorology (BOM).[10] Data are assigned to all cycle counters using measures from the Sydney Airport Metropolitan monitoring station.[11]

3.4 Bushfires

Bushfires are frequent events in south-eastern Australia and are acknowledged to contribute significantly to air quality problems in Sydney. Bushfires emit particulate matter, carbon monoxide, carbon dioxide, oxides of nitrogen and volatile organic compounds which in the presence of sunlight becomes photochemical smog. It is well-established that depending on meteorological conditions, smoke from bushfires can travel a very long distance (i.e. over 2000 miles) and has a mean lifetime of 8 to 20 days (Glatthor et al. (2013), Wotawa and Trainer (2000)). For instance, Forster et al. (2001) find a clear link between Canadian forest fires, O_3 and CO concentrations over Europe during August 1998. DeBell et al. (2004) find that

triggered by the forecast value of ozone.

[10] Data are found at: http://www.bom.gov.au/climate/data/

[11] The Sydney airport weather station is located close to the downtown of Sydney and has the most complete weather data. Given that varying distances between the airport and individual counters may cause measurement error concerns, we also assigned weather conditions to stations based on GPS coordinates and find no significant difference in results. To assuage concerns about the possibility of including too many controls in regressions - which could increase the standard error of estimated coefficients and so impact implied significance - we also estimate a stripped-down version of the model excluding weather controls. Results are in 5.4.

bushfires in Quebec in early July 2002 had significant influences on O_3, CO and $PM_{2.5}$ concentrations in both urban and rural areas of the east coast of the United States. Glatthor et al. (2013) show that pollutants from bushfire in early February 2009 in southeast Australia had significant negative impacts on the level of air quality in northeastward of New Zealand after 3 to 4 days.

Bushfires typically occur in the dry, sparsely populated bush areas of Boorowa and Hume, several hundred miles to the south-west of the city. More specifically, because of hot dry conditions, PM from bushfire events in Australia can transport vast distances, and affect the air quality level of areas far from their source (Confalonieri et al. (2007)). Notably, previous works such as Chen et al. (2006), Morgan et al. (2010), Jalaludin et al. (2000) and Smith et al. (1996) provide evidence of the statistically significant causal link between bushfire smoke (particularly O_3 and PM_{10}) and health outcomes in Australian cities. In more recent work, Johnston et al. (2011) show that bushfires in the Eucalypt forests to the west of Sydney significantly increased PM and O_3 concentrations of the city and were associated with a 5% increase in non-accidental mortality for a period of 1994 - 2007.

In this study we use bushfire activity as an instrument for air quality. Bushfire data is obtained from the NSW Rural Fire Service (RFS) and Romsey Australia.[12] For each fire, the size and its distance from the city of Sydney was obtained from the records of the Australian Emergency Management Institute (AEMI).[13]

4 Methodology

4.1 OLS

To estimate short-run direct avoidance behavior, we begin by examining the effect of alerts on daily cycle counts. The baseline fixed-effects model is:

$$\log(cycling)_{it} = \beta_1 alert_t + aqi_{it}\gamma_1 + W_{it}\delta_1 + \Phi_i + \phi_t + \epsilon_{it} \tag{1}$$

The dependent variable, $cycling_{it}$ is the number of bicycles counted at counter i on date t. The variable of interest is $alert_t$ which is a dummy variable that takes the value one on an alert day, zero otherwise. aqi_{it} is air quality index.[14] W_{it} is a vector

[12] Data are found at: http://home.iprimus.com.au

[13] Data are found at: http://www.emknowledge.gov.au

[14] The daily AQI is calculated using maximum 1-h average of pollutant concentrations during the 24 hour period. To better control for the actual level of air pollution in addition to the AQI composite, for robustness check we include average daily level of O_3, CO, NO_2, PM_{10} and $PM_{2.5}$ in the regressions. Potentially this could increase the standard error of estimated coefficients and so affect the significance of our results. The results, however, are shown to be quite insensitive to

of daily weather variables that we have already noted might have a direct impact on cycling behavior: maximum temperature, maximum temperature squared, average air temperature, precipitation, relative humidity, solar exposure, number of hours of bright sunshine and wind speed. Counter fixed-effects and time-fixed effects are Φ_i and ϕ_t, respectively. In particular, ϕ_t is a vector that includes dummies for day of week, holidays and year-month. ϵ_{it} is an error term. Throughout the paper error terms are clustered on counters to account for within-counter error correlations.[15]

When alerts are repeated on consecutive days, Graff Zivin and Neidell (2009) show evidence of a strong rebound effect - at least for the leisure activity of visiting a zoo. This sort of result, if more general, could have important implications for the operation of an alert program, with the principal needing to be aware of the possibility of ‘alert fatigue’. The extent if any of the rebound is likely to be sensitive to the activity in question. A zoo visit is an infrequent and in most cases easy-to-postpone activity, whereas getting to work by bicycle, for example, might not be. To see how far their results carry over into our setting, the model is expanded to a 2-day model as follows:

$$\begin{aligned} \log(cycling)_{it} \quad = \quad & \beta_1 alert_t + \beta_2 alert_{t-1} + alert_{t-1} \times alert_t \beta_{12} \\ & + aqi_{it}\gamma_1 + aqi_{it-1}\gamma_2 + W_{it}\delta_1 + W_{it-1}\delta_2 + \Phi_i + \phi_t + \epsilon_{it} \qquad (2) \end{aligned}$$

where $alert_{t-1}$ is lagged alerts. As noted by Graff Zivin and Neidell (2009), the interaction of current ($alert_t$) and lagged ($alert_{t-1}$) allows for the possibility that the impact of an alert on date t is sensitive to the presence of an alert on date $t-1$. If alerts are issued on two successive days, $t-1$ and t, the effect of the second day's alert on cycling is $\beta_1 + \beta_{12}$. However the impact of one-day alert is still β_1 since for a one-day alert we have $alert_{t-1} = 0$.

4.2 Causal Identification

Our coefficient of interest is that on the variable *alert*, which is exogenously assigned and observed without measurement error. In particular, as we discuss, air quality alerts are established the preceding day based on a forecast of air quality,

inclusion of the pollution variables.

[15]Angrist and Pischke (2008) suggest that to have a fairly accurate variance formula, at least we need to have 42 clusters, while we only have 26 clusters. We repeat our analysis using block bootstrapping. Block-bootstrapped standard errors deliver similar results. In addition, we repeat our analysis using a two-way cluster on both counter and date. The statistical significance of our results is unchanged.

are carefully recorded, and apply to the entire city. However, we are concerned that the OLS point estimate of *alert* is contaminated because of endogeneity in air quality level (*aqi*). As we describe, we model cycling behavior as a function of both alerts (established the prior day) and concurrent air quality. The two variables are correlated, although not perfectly, because of errors in the process for forecasting air quality. Moreover, there are several reasons to think that air quality is measured with error, as well as potentially endogenous. Although the main alert variable is exogenous, the correlation between the endogenous air quality variable and the alert variable will lead to bias in OLS estimates of the effect of alerts on cycling behavior (we explain this point more formally later in this section).

There are several reasons to think that our air quality measure could be measured with error and endogenous. First, meteorological factors can be expected to affect cycling decisions directly - people may prefer to cycle on days that are warm (but not too warm), dry, etc.. Connolly (2008) and De Freitas et al. (2008) have shown that, for a variety of outdoor activities, weather matters. Equally, weather can be expected to impact air quality. Ozone is not a pollutant that is directly emitted by any source, but rather arises from the chemical reaction of nitrogen oxides and volatile organic compounds when exposed to sunlight. Furthermore pollutants can be washed from the air by rain, and smog once formed can be dispersed by wind. Although we can try to control for weather conditions, it is likely to be difficult to fully control for environmental confounders at sufficient spatial and temporal level (Moretti and Neidell (2011)).

Second, as noted by Neidell (2009), assigning pollution variables to each counter using interpolation techniques might result in measurement error for two reasons. First, air pollution levels may vary between regions. Second, individuals can move between regions in the course of a day, and we do not know in a sufficiently detailed way *where* they spend their time and therefore to what level of pollution they have been exposed when making decisions about cycling. Previous studies such as Jacquemin et al. (2013), Lleras-Muney (2010) and Schlenker and Walker (2011) find that estimation of the effect of air pollution on health is quite sensitive to the methods used in assigning the pollution exposure variables to individuals.

Third, there is a possibility that individuals reduce their exposure to pollution by substituting to more emissions-intensive activities (for example by switching from cycling to driving). Therefore pollution exposure is potentially endogenous in the framework of our study.

To reiterate, our main dependent variable of interest throughout the paper is a dummy variable for alerts indicating the existence of an alert on a particular day. This does not suffer from measurement error or endogeneity. In fact, $alert_t$ is forecast-driven and it is determined by the value of $\mathbb{E}_{t-1}[AQI_t]$. As $\mathbb{E}_{t-1}[AQI_t]$ and AQI_t are likely correlated, it is sensible to assume that AQI_t and $alert_t$ are correlated.[16] Because of correlation between air quality and alerts, our OLS estimate of the effect of alerts is biased as a result of endogeneity in the air quality variable. To show the bias in the estimated coefficient on $alert$ when aqi and $alert_t$ are correlated consider the following simple equation:

$$\log(cycling) = \beta alert + \gamma aqi + \epsilon, \tag{3}$$

in which $alert$ is randomly assigned while aqi is subject to measurement error. We show that $\hat{\beta}$ is unbiased only if these two regressors are uncorrelated. In particular, consider the formula for $\hat{\beta}$:

$$\hat{\beta} = \frac{var(\tilde{aqi})cov(log(cycling), alert) - cov(alert, \tilde{aqi})cov(log(cycling), \tilde{aqi})}{var(alert)var(\tilde{aqi}) - cov(alert, \tilde{aqi})^2} \tag{4}$$

where $\tilde{aqi} = aqi + u$ is the measured air quality level, and u is the error in measurement. Thus we can write:

$$\begin{aligned} plim\hat{\beta} &= \frac{\sigma^2_{aqi}(\beta\sigma^2_{alert} + \gamma\sigma_{alert,aqi}) - \sigma^2_{alert,\tilde{aqi}}(\gamma\sigma^2_{aqi} + \beta\sigma_{alert,aqi})}{\sigma^2_{aqi}(\sigma^2_{alert} + \sigma^2_u) - (\sigma_{alert,\tilde{aqi}})^2} \\ &= \frac{\beta(\sigma^2_{aqi}\sigma^2_{alert} - \sigma_{alert,\tilde{aqi}}\sigma_{alert,aqi}) + \gamma\sigma^2_{aqi}(\sigma_{alert,aqi} - \sigma_{alert,\tilde{aqi}})}{\sigma^2_{aqi}(\sigma^2_{alert} + \sigma^2_u) - (\sigma_{alert,\tilde{aqi}})^2} \end{aligned} \tag{5}$$

for simplicity assume that $alert$ is correlated with aqi but not u, thus $\sigma_{alert,aqi} = \sigma_{alert,\tilde{aqi}}$ so we can simplify $\hat{\beta}$ as follows:

$$plim\hat{\beta} = \frac{\beta(\sigma^2_{aqi}\sigma^2_{alert} - (\sigma_{alert,aqi})^2)}{\sigma^2_{aqi}(\sigma^2_{alert} + \sigma^2_u) - (\sigma_{alert,aqi})^2} = \beta\lambda \tag{6}$$

which proves when regressors are correlated, the endogeneity of one regressor will affect the consistency of coefficients on other regressors. In particular, based on the preceding, $\hat{\beta}$ is biased downwards (i.e., $\lambda < 1$). Therefore while $alert$ is determined exogenously it is essential to control for potential endogeneity of aqi_t. To alleviate this problem, we instrument for AQI using bushfires.

[16] In our sample the correlation between $alert_t$ and aqi_t and aqi_{t-1} is respectively 0.35 and 0.37.

4.3 IV

Our IV approach is intended to eliminate the source of bias in OLS that we describe in the prior section. Encouragingly the results prove quite similar (indeed identical in terms of sign and significance) across the IV and OLS methods. In addition results are robust to a variety of specification checks. The first stage of our IV approach:

$$
\begin{aligned}
aqi_{it} &= \alpha_1 bushfire_t + \alpha_2(bushfire_t \times size_t) + \alpha_3(bushfire_t \times distance_t) \\
&\quad + W_{it}\delta_1 + \psi_t + \Psi_i + \upsilon_{it} \qquad (7)
\end{aligned}
$$

where $bushfire_t$ is a dummy variable which is one for the date when there was an active bushfire affecting Sydney air quality and zero otherwise. The variable $size_t$ is a measure of the size of the fire in hectares - which can sensibly be regarded as a proxy for the amount of pollutants it is generating - and $distance_t$ is the distance between an active fire and the city. The first stage regression is run with different combinations of these elements without changing the qualitative results.

We adopt bushfire activity as an instrument for air quality. In the basic version, we account for the incidence of active bushfire using a dummy for date that was active fire in the vicinity of Sydney on a particular date and the size of fire. In other versions we also account for the distance of fire from the city.[17]

Using $bushfire$ as instrument requires that several conditions be satisfied. Essentially, bushfire must impact air quality ($cov(bushfire_t, AQI_{it}) \neq 0$) while it should not have any direct influence on cycling choice other than through it's effect on air quality. In other words, the exclusion restriction implies that bushfire should be orthogonal to other unobservable factors affecting demand for cycling ($cov(bushfire_t, \epsilon_{it}) = 0$).

Various considerations point to bushfires being a strong instrument for air quality. First, although hot and dry weather provides conditions conducive to fire, they are a quasi-random event requiring a trigger - either natural or a human action. Thus, their occurrence cannot be timed perfectly and it is sensible to assume that $bushfire$ is uncorrelated with other unobservable factors that might affect the cycling decision. Second, as discussed in Section 3.4, it is well-established that bushfire activity has a significant negative impact on Sydney air quality (Johnston et al. (2011), Glatthor et al. (2013), Confalonieri et al. (2007) and Morgan et al.

[17] We experiment with lags of bushfires of up to five days, but only concurrent bushfires have a statistically significant impact.

(2010)).

Third, it is sensible to assume that bushfires do not have any direct impacts on cycling behavior except via their effect on air quality. As discussed in 3.2, in order to forecast the level of air quality, expected emissions from bushfires are routinely assessed by NSW OEH and all information about impacts of bushfires' smoke on air quality is incorporated into air quality alerts. Likewise, it is logical to assume that all possible impacts of bushfire smoke on cycling demand is completely absorbed by air quality alerts since bushfires typically occur a great distance from the city (an average of 589 miles in this study) and smoke from such fires are almost never observable in Sydney. It is important to mention that during the period of this study NSW residents were not provided with any further information about bushfires' smoke (even if they should have wanted it) until the NSW OEH website was updated in September 2014 to incorporate a burn notice explicitly.[18]

4.4 Sub-sample analyses

It could be hypothesized that leisure cyclists and those who commute by bicycle react to an alert in different ways. In particular a leisure ride may be easier to substitute away from, or to postpone.

Of course the counters extract no information on the *motives* of the riders whose bicycles are counted. However, if the hypothesis is correct then we would expect to see different reactions in aggregate bicycle movements on different *types* of cycle-path.

In light of this, we seek to categorize the 26 routes on which the counters are located into two types - 'leisure' and 'commuter' - and re-estimate our regressions for each sub-sample of counters. For robustness we categorize routes in two different ways;

(1) First, by comparing the relative density of bicycle traffic on a particular route during the week versus on the weekend. Different counters have very different day-of-the-week profiles. In Figure 3, for example the upper panel depicts the daily distribution of average number of cyclists by day of week from counter 1 (Harbour Bridge), while the lower panel is the profile for counter 31 (Como Bridge). If the average number of cyclists at a counter is higher on the weekends rather than weekdays that route is classified as 'leisure', and 'commuter' otherwise. Using this criterion, 11 of the 26 active stations are classified as leisure and 15 as commuter.

(2) Second, by comparing the density of traffic at different times of day - in

[18]This notice however, does not provide any information about smoke concentrations of bushfire and residents are still encouraged to take proper action accounting for air quality information.

particular the pronouncedness of the peak in cycling trips during the traditional morning and evening peak hours (7am - 10am and 4pm - 7pm). Again, the counters vary substantially in the timing of traffic through the day. For example shown in Figure 4, in the upper panel (for counter 1 (Harbour Bridge)) the flow during the morning and afternoon peaks are very strong, compared to the lower panel (counter 8 (Falcon Street)). Routes are categorized into 'leisure' and 'commuter' adopting the following criterion: If the peak hours cycling traffic exceeds 80% of total weekdays traffic, we classified a route to be commuter, and leisure if it is below 80%. Applying this criterion, 5 and 21 stations are classified as leisure and commuter, respectively.

5 Results

Figure 5 provides some graphical motivation for our regression analysis. In particular it shows the relationship between average cycle counts over all counters and days and AQI on bins of days *with* (black triangles) and *without* (grey circles) an alert. There are no controls here for the various confounding factors, so it is difficult to derive causal inference directly from the figure. However we can fit by OLS lines through the black triangles (the black line) and separately through the grey circles (the grey line) and see that the former clearly lies below the latter. This provides initial encouragement for the view that alerts are effective in discouraging cycling.

Statistically - and again we emphasize that this is without any controls - the mean number of cyclists on days with an alert is between 15% and 24% lower than days without.[19]

The figure usefully illustrates an important aspect of our research design, which has been alluded to earlier in the paper. In particular, it shows the imperfect concordance between the air quality and the alert status. Air quality alerts are issued when the *forecast* air quality index exceeds 100. The figure shows that there are a number of days in which alerts were not issued in which actual air quality does exceed 100, as well as a number of days in which an alert was issued, but air quality is inferior to 100. Our model of cycling behavior controls for both the alert status and the concurrent air quality level.

As shown in Figure 5 (and also in our full point estimates tables presented in the appendix (Tables A.1 and A2)) there is a positive relation between AQI and cycling. This is not the main concern of our paper, however, it might arise because of the confounding effect of weather variables. For example if people spend more

[19]To better show the difference, we limit the sample in this figure to AQI values between 50 and 200.

time on outdoor activities on a sunny day, demand for cycling will increase while this would also lead to an increase in AQI level since temperature and sunlight are the main precursors of ozone formation.

To further explore this, we also regress cycling on AQI, time and cycling fixed effects. As presented in Table A.3 of appendix, there is a positive and statistically significant relation between AQI and cycling demand suggesting that cyclists might be unaware of the fact that ozone formation (as the main pollutant in Sydney) is higher on a warmer, sunny day. This reinforces that alerts are effective in a sense that issuing an alert can inform people about negative health impacts of having strenuous activities such as cycling on polluted days.

5.1 OLS

Ordinary Least Squares estimation results based on the Equation (1) are presented in Table 3 and full point estimate results are reported in Table A.1 of appendix. The specifications in all three columns contain the vector of weather and pollution controls specified earlier, in addition to route and time fixed effects.

Column 1 provides the 'take away' from this part of the analysis. An alert decreases cycle traffic by 14.1%, significant at the 0.1% level.

Columns 2 and 3 present results of separate OLS regressions run on weekday and weekend-day samples. The independent effect of an alert is substantially larger on weekends, reducing cycle traffic by 26.5% which is significant at the 0.1% level. We return to more careful consideration of the impact of alerts on leisure versus commuter traffic later in the paper.

5.2 IV

The regression results using a fixed-effect instrumental variable estimator are reported in Table 4 and full point estimates of the same table are presented in Table A.2 of appendix.[20]

The upper part (Panel A) contains the relationship between AQI and bushfires – the first stage regression results based on the Equation (3). Panel B provides the coefficient estimate on the *alert* variable from the second-stage estimation. A full suite of controls is used in both stages.

[20]As can be seen in Table A.2, AQI point estimates are positive when bushfire (Column (1)) and bushfire and size (Column (2)) are chosen as our sets of instruments while there is a statically negative relation between AQI and cycling demand in Column (3). It is important to mention that overall conclusion of this paper for all our IV results is insensitive to the choice of instrument. However, we did not choose Column (3) as our preferred specification since Column (2) appears to be a stronger instrument, specifically for our sub-sample analysis.

We report three variations to help provide a sense of robustness. In each case we estimate - as expected - a larger impact of alerts than the 14.1% reduction in use implied by OLS (we show in Section 4.2 that the OLS coefficient is biased towards zero).

In column 1 the single instrument bushfire (the yes/no dummy capturing whether a bushfire was burning on the date in question) is used. The issuance of an alert is estimated to reduce cycle traffic by 29.3%, significant at the 1% level.

Columns 2 and 3 adjust the first-stage estimation to allow first for the size of the fire in hectares, second for the distance of the fire from the city. The implied independent impact of the issue of an alert is to reduce cycle traffic by 35.1% and 13.2% in the two cases respectively. Both estimates are significant at the 5% level.

The statistics in Panel C point to the quality of the instruments used. It is worthwhile to note that for all other IV regressions, bushfire and size are chosen as our preferred specification since the F-statistic for excluded instruments and Hausman test suggest that bushfire and size are statistically stronger instruments, though the results of other instruments are quite similar to each other.[21]

5.3 2-day model: Alert fatigue

There has been some concern amongst policy-makers of the possibility of alert fatigue - that the impact on behavior may be substantial on the first day that an alert is issued, but decline if alerts are issued on subsequent days.

Table 5 shows the OLS and IV results for a 2-day model. In the preferred IV specification, when alerts are issued for two successive days the alert on the second day is estimated to reduce cycle traffic by just 1.6% (statistically insignificant at the 5% level).[22] It should be noted, however, that the number of consecutive-day alerts in our data set is very small - occurring on only seven occasions in the five year period covered by this study. As such we need to be wary about reading much into either the value of the coefficient or the lack of significance.

[21]Under the null hypothesis of the Hausman test, the specified endogenous regressors can be treated as exogenous, and the test statistic is distributed as chi-squared with degrees of freedom equal to the number of regressors tested. The Hausman test for bushfire and size and bushfire, size and distance has respectively a p-value of 0.000 and 0.4126. This implies that the difference between OLS and IV estimation is statistically significant when bushfire and size are instrumented for air quality. Furthermore, the F-statistics from the first stage for excluded instruments are calculated to test the hypothesis stating whether the excluded instruments are irrelevant. The magnitude of F-statistics indicate that all our instruments are statistically strong and relevant.

[22]The second day response is $\beta_1 + \beta_{12}$, the significance of this composite coefficient being tested by means of a joint test.

5.4 OLS and IV robustness

We conduct several robustness checks on our results. To provide evidence suggestive of robustness of our approach in controlling confounders, we re-estimate the preferred specifications excluding weather controls. We also include daily measures of O_3, NO_2, CO, PM_{10}, $PM_{2.5}$ concentrations and re-estimate our regression. This is because it is possible that cycling decisions are based on individual pollution levels rather than aggregate measure of air pollution (AQI).[23]

As already noted, pollution and weather variables are likely sources of confounding and accounting properly for their impacts on cycling demand is one of the main methodological challenges in estimation in this context. Insofar as the main coefficient estimates do not change excessively when controls for these variable are excluded, it can be claimed that the approach taken does a good job controlling for the effect of confounding variables (following Moretti and Neidell (2011)). We can conclude that omitted variable bias is unlikely to be a substantial concern in our estimation.

Table 6 reports the results of nine separate regressions (five OLS and four IV). In assessing the results, our primary focus is on the stability of the IV estimates. Column 1 reproduces coefficient estimates from the preferred specifications in Tables 3 and 4.

In Column 2, the regression is re-run including individual pollutant levels. In Column 3, we re-estimate our regressions excluding weather controls. The absolute value of the estimated coefficient on alerts using the preferred IV approach falls from 0.351 to 0.143 by inclusion of co-pollutants. It falls to 0.303 with the exclusion of weather controls (Column 3). In column 4, AQI_t is omitted from our regression, in this case we do not need to instrument for AQI since alert is determined exogenously. As can be seen the absolute value of $alert_t$'s point estimate remains statistically significant and has slightly changed.

Despite our efforts to ensure the exogeneity of $alert_t$, there still may remain concerns about potential endogeneity since we are unable to fully control for the effect of all confounders. One of the potential omitted variable is major sports events such as the marathon. The presence of such an event may raise (or lower) contemporaneous AQI, and thus make an alert the following day more (or less) likely. The day following such an event, demand for cycling may be lower than usual because cyclists may feel tired as a result of attending the event. Therefore

[23] Although excluding these variables might lead to omitted variable bias, we did not include them in our main regressions because this will potentially lead to multiple endogenous variables problem.

major sport events can in fact affect both cycling and pollution levels. In this case our IV strategy is not helpful in controlling for the effect of confounders. In order to address this type of situation, column 5 includes AQI_{t-1} as an additional control. In this way variation in $alert_t$ is only due to the difference between $\mathbb{E}_{t-1}[AQI_t]$ and AQI_t. It is important to mention that for our IV regression, we also instrument for AQI_{t-1} using $bushfire_{t-1}$ and $size_{t-1}$. As shown, our results are insensitive to inclusion of AQI_{t-1}, confirming that $alert_t$ is as good as random since it is a forecast driven variable and the effect of AQI_{t-1} is fully taken into account in forecasting $alert_t$. Together, these results suggest that our approach controls well for potential unobserved effects of pollution and weather factors since the coefficient estimates remain the same in sign and significance and similar in magnitude.

We also explore robustness of the regression results to potential non-linearity in the relationship between air quality and demand for cycling. Table 7 reports estimation results allowing for quadratic form of the air quality index variable. For the IV regression we also instrument for the quadratic form of AQI by bushfire and size. In the basic OLS estimation, controlling for the quadratic formulation leaves the estimated coefficient remain almost unchanged whilst in the IV case the coefficient changes from -0.35 to -0.260, unchanged in sign and significance.[24]

5.5 Sub-sample analyses

Results for sub-sample analyses are collated in Table 8. Each column summarizes the key outputs from IV estimation on a sub-sample of the data.[25]

It is clear that we might expect different behavioral response depending on the purpose of journey, in particular a leisure ride versus use of a bicycle as a means of getting to work. The opportunities for modal or inter-temporal substitution may vary substantially between purposes.

To try to get at this, the sample is divided up in three different ways. The underlying difficulty is that the counter measures only cycle movements, and the purpose of the journey is unobserved by the researcher. While our various categorizations will provide indicative evidence none will provide for a 'clean' separation of leisure from commuter riders. As usual what we are looking for is consistency of results across the various sub-sample treatments.

[24]A Durbin-Wu-Hausman test indicates that the difference between IV and OLS is statistically significant.

[25]It is worthwhile to note that for all IV regressions, bushfire and size are instruments for air quality since the F-statistics for excluded instruments suggest that bushfire and size are statistically stronger instruments for subsample regressions. Running other combinations of the instruments generated very similar results that we do not report.

Columns 1 and 2 summarize separate analysis of weekday and weekend cycle use (throughout the paper weekend also includes public holidays). The results of the second-stage regression reported in Panel B show that the issuance of an alert reduces cycle use by 49.5% on weekends, but only 30.9% on weekdays. A Chow test presented in Panel C shows that we can reject the null hypothesis that weekends and weekdays point estimates are the same. This is consistent with the observation that a leisure ride is easier to cancel or postpone than is a trip to work.

The other results in Table 8 focus not on divisions of the data-set by time, but two different ways in which we attempt to categorize *routes* into commuter and leisure-intensive routes.

In Columns 3 and 4 the cycle routes are divided according to the pattern of cycle movements *across days of the week*, with those routes more heavily used on weekdays being categorized as 'commuter'. The coefficient estimates in Panel B point to the independent effect of an alert being to reduce cycle use by statistically significant 40.1% on leisure routes and 23.7% on commuter routes.

In columns 5 and 6 the cycle routes are divided according to the pattern of cycle movements *within each day*, with those experiencing more than 80% of their usage during peak hours on weekdays being categorized as commuter routes. The coefficient estimates in Panel B point to the independent effect of an alert being to reduce cycle use by statistically significant 38.6% on leisure routes but only 20% on commuter routes. For both specifications we also present a Chow test in Panel C indicating that point estimates for commuter and leisure routes are statistically different.

None of the categorizations are perfect in separating leisure from journey to work trips. Somebody riding on a Saturday may be on their way to work, for example - though that is less likely than would be the case if observed on a Monday. However the striking similarity in estimated coefficients across the three categorizations points to robustness, with the reduction in leisure ridership induced by an alert being in the range 38 to 40%, commuting in the range 20 to 23%.

6 Conclusion

The empirical analysis provides compelling evidence that air quality alerts issued in Sydney, Australia are highly effective in encouraging people to get off their cycles. Exact estimates have naturally varied across specification and sub-samples, but the results consistently point to a response around the 15 to 35% level. Cycling for leisure appears to be much easier to discourage than cycling to work. There is weak evidence of alert fatigue, based on a very small sample.

That people react - adjust their behavior when armed with pertinent information - is central to these sorts of information-based policy interventions working. In particular, it is vital that when air pollution levels are raised people reduce or eliminate participation in vigorous outdoor activities. This is the first study to use administrative data to show that they do (and indeed only the second overall, following a small-scale park bench study carried over just 35 days in Atlanta.) Estimating the health benefits of the change in behavior is beyond the scope of the paper, and would pose the additional challenge of determining the activity into which people substitute when they stop cycling.

Naturally a study of this sort involves a particular application, namely cycling in Sydney. As such there are obvious questions as to how far the results will generalize to other settings - maybe an Australian will heed a public health warning, where a German wouldn't. This points to the utility of further work in other contexts. But given the increasing reliance being put on alert schemes and other information-provision interventions, evidence that they work - and work well - in discouraging vigorous outdoor activity in at least *one* setting is encouraging to have.

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Table 1: New South Wales Air NEPM Standards

	Average period	Maximum concentration
Carbon monoxide	8 hours	9.0 (ppm)
Nitrogen dioxide	1 hours	0.12 (ppm)
Photochemical oxidants (as ozone)	1 year	0.03 (ppm)
	1 hour	0.10 (ppm)
	4 hours	0.08 (ppm)
Sulfur dioxide	1 hour	0.20 (ppm)
	1 day	0.08 (ppm)
Lead	1 year	0.50 ($^{\mu g}/_{m^3}$)
Particles as PM10	1 day	50 ($^{\mu g}/_{m^3}$)
Particles as PM2.5	1 day	25 ($^{\mu g}/_{m^3}$)

Source: NSW EPA.

Table 2: Summary Statistics for May 2008 - September 2013

	Mean	Std. Dev.
Cycling	353.7	474.4
Weekdays	373.0	533.2
Weekends	305.3	270.5
Alert Frequency (%)	0.013	0.114
Two Successive Alerts Frequency (%)	0.0038	0.013
Bushfire Frequency (%)	0.027	0.163
Bushfire size (ha)	1988.78	866.64
Bushfire distance (km)	1092.56	1296.94
Explanatory Variables		
AQI	55.58	38.80
Carbon monoxide 1-h (pphm)	0.349	0.170
Ozone 1-h (pphm)	0.032	0.014
Nitrogen dioxide 1-h (pphm)	0.967	0.455
Particles as PM10 1-h ($^{\mu g}/_{m^3}$)	19.17	8.69
Particles as PM2.5 1-h ($^{\mu g}/_{m^3}$)	5.944	3.6
Total Daily Solar Exposure ($^{MJ}/_{m^2}$)	15.99	7.6
Precipitation (mm)	0.33	1.78
Maximum temperature (°C)	22.73	4.97
Daily Average of Air temperature (°C)	15.2	4.72
Relative Humidity (%)	77.65	13.3
Wind speed ($^{km}/_{h}$)	16.41	8.61

Sources: Cycling data obtained from NSW Department of Roads and Maritime Services. Alert and pollutant data collected from the NSW Office of Environment and Heritage. Weather data collected from Australia Bureau of Meteorology.

Table 3: OLS Regression Results

	(1) Total	(2) Weekdays	(3) Weekends
Alert	-0.141***	-0.162***	-0.265***
	[0.0292]	[0.0422]	[0.0376]
Controls for Weather	Y	Y	Y
Control for AQI	Y	Y	Y
Time Fixed Effect	Y	Y	Y
Cycling Routes Fixed Effect	Y	Y	Y
Observations	28452	20331	8121
R^2	0.261	0.308	0.331

The dependent variable is $log(cycling)$. Clustered by counters, standard errors in brackets. Weather covariates include temperature, maximum temperature, minimum temperature, humidity, solar exposure, wind speed, precipitation and number of hours of bright sun. Pollution covariate includes air quality index. Time dummies include day of week, year-month and holidays.
* significant at 5% ** significant at 1% *** significant at 0.1%.

Table 4: Instrumental Variable Regression Results

	(1)	(2)	(3)
A.First Stage $^{(a)}$			
Bushfire	11.0445***	5.315**	-4.063
	[1.4546]	[2.7167]	[3.1347]
Bushfire*Size	-	0.00287***	0.00463***
	-	[0.0011]	[0.00109]
Bushfire*Distance	-	-	0.0044***
	-	-	[0.0008]
B.Second Stage $^{(b)}$			
Alert	-0.293***	-0.351***	-0.132**
	[0.0575]	[0.0600]	[0.0476]
Controls for Weather	Y	Y	Y
Control for AQI	Y	Y	Y
Time Fixed Effect	Y	Y	Y
Cycling Routes Fixed Effect	Y	Y	Y
C. F-Statistic for Excluded Instruments $^{(c)}$	57.65	33.20	32.17
Wu-Hausman	10.822	19.794	0.671
(P-value)	(0.0010)	(0.000)	(0.4126)
Observations	28452	28452	28452

Note: (a) Dependent variable is AQI. (b) Dependent variable is $log(cycling)$. (c) The values reported are the Angrist-Pischke multivariate F-statistics (Angrist and Pischke (2009)). Clustered by counters, standard errors in brackets. Weather covariates include temperature, maximum temperature, minimum temperature, humidity, solar exposure, wind speed, precipitation and number of hours of bright sun. Pollution covariate includes air quality index. Time dummies include day of week, year-month and holidays.
* significant at 5% ** significant at 1% *** significant at 0.1%

Table 5: Impact of Two Successive Day Alerts on Cycling Activity

	(1) OLS	(2) IV
First day response	-0.169***	-0.247***
	[0.0315]	[0.0474]
Second day response	-0.05	-0.049
	[0.0256]	[0.0492]
Controls for Weather	Y	Y
Control for AQI	Y	Y
Time Fixed Effect	Y	Y
Cycling Routes Fixed Effect	Y	Y
Observations	28076	28076

Notes: Dependent variable is $log(cycling)$. Lag of AQI is also instrumented by bushfire and size. Clustered by counters, standard errors in brackets. Weather covariates include temperature, maximum temperature, minimum temperature, humidity, solar exposure, wind speed, precipitation and number of hours of bright sun. Pollution covariate includes air quality index. Time dummies include day of week, year-month and holidays.
* significant at 5% ** significant at 1% *** significant at 0.1%

Table 6: Sensitivity of Results to Weather and Pollution Factors

	(1)	(2)	(3)	(4)	(5)
A. OLS Regression$^{(a)}$					
Alert	-0.141***	-0.124**	-0.298***	-0.136***	-0.142***
	[0.0292]	[0.0485]	[0.0361]	[0.0288]	[0.0291]
B. IV Regression$^{(b)}$					
Alert	-0.351***	-0.143***	-0.303***	-	-0.355***
	[0.0600]	[0.0382]	[0.0452]	-	[0.0585]
Controls for Weather	Y	Y	N	Y	Y
Control for AQI_t	Y	Y	Y	N	Y
Control for AQI_{t-1}	N	N	N	N	Y
Controls for Pollution	N	Y	Y	N	N
Time Fixed Effect	Y	Y	Y	Y	Y
Cycling Routes Fixed Effect	Y	Y	Y	Y	Y
F- Statistic for Excluded Instruments $^{(c)}$	184.09	102.03	100.93	-	51.65
Durbin-Wu-Hausman	19.794	5.895	0.080	-	3.779
(P-value)	(0.000)	(0.0152)	(0.765)	-	(0.052)
Observations	28452	28452	28452	28452	28452

Notes: (a) and (b) Dependent variable is $log(cycling)$. (c) The values reported are the Angrist-Pischke multivariate F-statistics (Angrist and Pischke(2009)). Clustered by counters, standard errors in brackets. Weather covariates include temperature, maximum temperature, minimum temperature, humidity, solar exposure, wind speed, precipitation and number of hours of bright sun. Pollution covariate includes air quality index. Time dummies include day of week, year-month and holidays. AQI_{t-1} in the fifth column is instrumented using lagged value of bushfire and size.
* significant at 5% ** significant at 1% *** significant at 0.1%.

Table 7: Robustness to Non-linear Relations Between Air Quality and Cycling

	(1)	(2)	(3)	(4)
	OLS	OLS	IV	IV
Alert	-0.141***	-0.155***	-0.351***	-0.260***
	[0.0292]	[0.0307]	[0.0600]	[0.0397]
Controls for Weather	Y	Y	Y	Y
Control for AQI	Y	Y	Y	Y
Time Fixed Effect	Y	Y	Y	Y
Cycling Routes Fixed Effect	Y	Y	Y	Y
Durbin-Wu-Hausman test	-	-	19.794	10.90
(p-value)	-	-	(0.000)	(0.001)
Functional Form	Linear	Quadratic	Linear	Quadratic
Observation	28452	28452	28452	28452

Notes: Dependent variable is $log(cycling)$. Quadratic form of AQI is also instrumented by bushfire and size. We are unable to estimate cubic and quartic form of AQI using IV regression since our model becomes under-identified. Clustered by counters, standard errors in brackets. Weather covariates include temperature, maximum temperature, minimum temperature, humidity, solar exposure, wind speed, precipitation and number of hours of bright sun. Pollution covariate includes air quality index. Time dummies include day of week, year-month and holidays.
* significant at 5% ** significant at 1% *** significant at 0.1%.

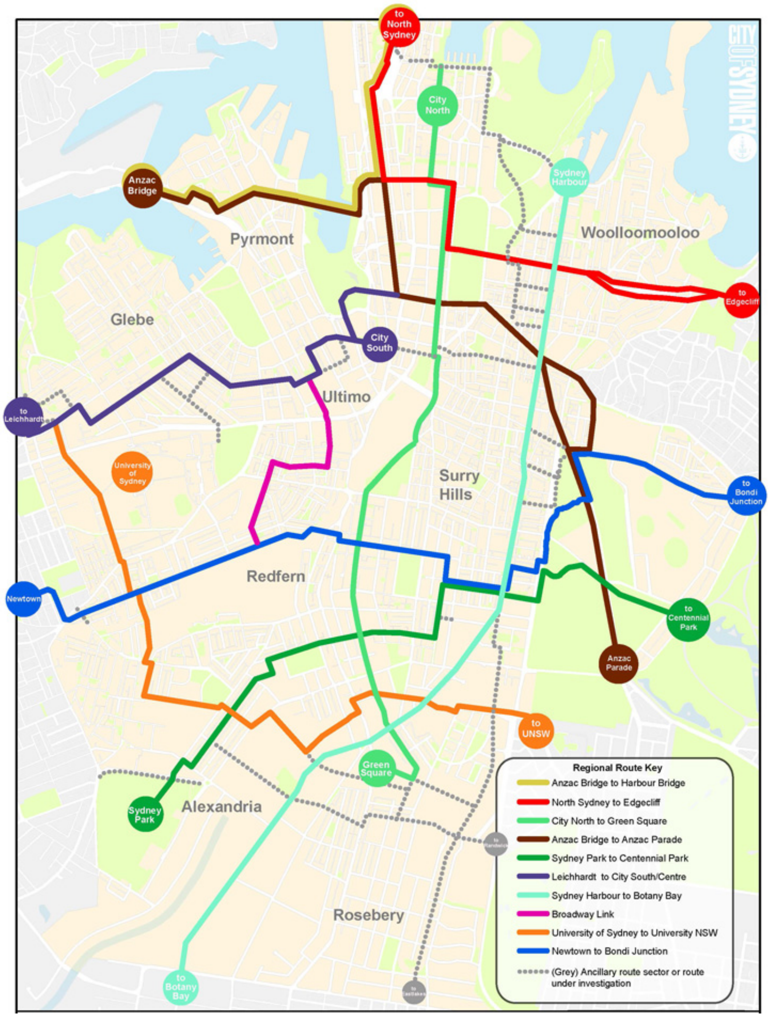
Table 8: IV Regression Results for Weekends vs. Weekdays and Leisure vs. Commuter routes

			Weekday density		Peak hour density	
	(1)	(2)	(3)	(4)	(5)	(6)
	Weekdays	Weekends	Commuter	Leisure	Commuter	Leisure
A. First Stage $^{(a)}$						
Bushfire	2.667	22.413***	6.584	5.918	18.927**	2.464
	[3.014]	[6.207]	[3.498]	[4.938]	[7.000]	[2.954]
Bushfire*Size	-0.0043***	-0.0048*	0.00243	0.0034*	- 0.00008	0.0034***
	[0.0013]	[0.0023]	[0.00126]	[0.0021]	[0.003]	[0.0011]
B. Second Stage $^{(b)}$						
Alert	-0.309***	-0.495***	-0.237***	-0.401***	-0.200**	-0.386***
	[0.0547]	[0.109]	[0.0676]	[0.0810]	[0.0724]	[0.0821]
Controls for Weather	Y	Y	Y	Y	Y	Y
Control for AQI	Y	Y	Y	Y	Y	Y
Time Fixed Effect	Y	Y	Y	Y	Y	Y
Cycling Routes Fixed Effect	Y	Y	Y	Y	Y	Y
F-statistic for Excluded Instruments $^{(c)}$	22.74	18.32	19.10	17.85	14.31	22.21
Wu-Hausman	16.408	2.490	3.764	17.816	8.147	15.469
(P-value)	(0.0001)	(0.1146)	(0.0524)	(0.000)	(0.0043)	(0.0001)
Chow test	7.48	7.48	7.67	7.67	9.97	9.97
(P-value)	(0.0062)	(0.0062)	(0.0024)	(0.0024)	(0.0016)	(0.0016)
Observations	20331	8121	16543	11898	5358	23094

]Notes: (a) Dependent variable is AQI. (b) Dependent variable is $log(cycling)$. (c) The values reported are the Angrist-Pischke multivariate F-statistics (Angrist and Pischke (2009)). Clustered by counters, standard errors in brackets. Weather covariates include temperature, maximum temperature, minimum temperature, humidity, solar exposure, wind speed, precipitation and number of hours of bright sun. Pollution covariate includes air quality index. Time dummies include day of week, year-month and holidays.

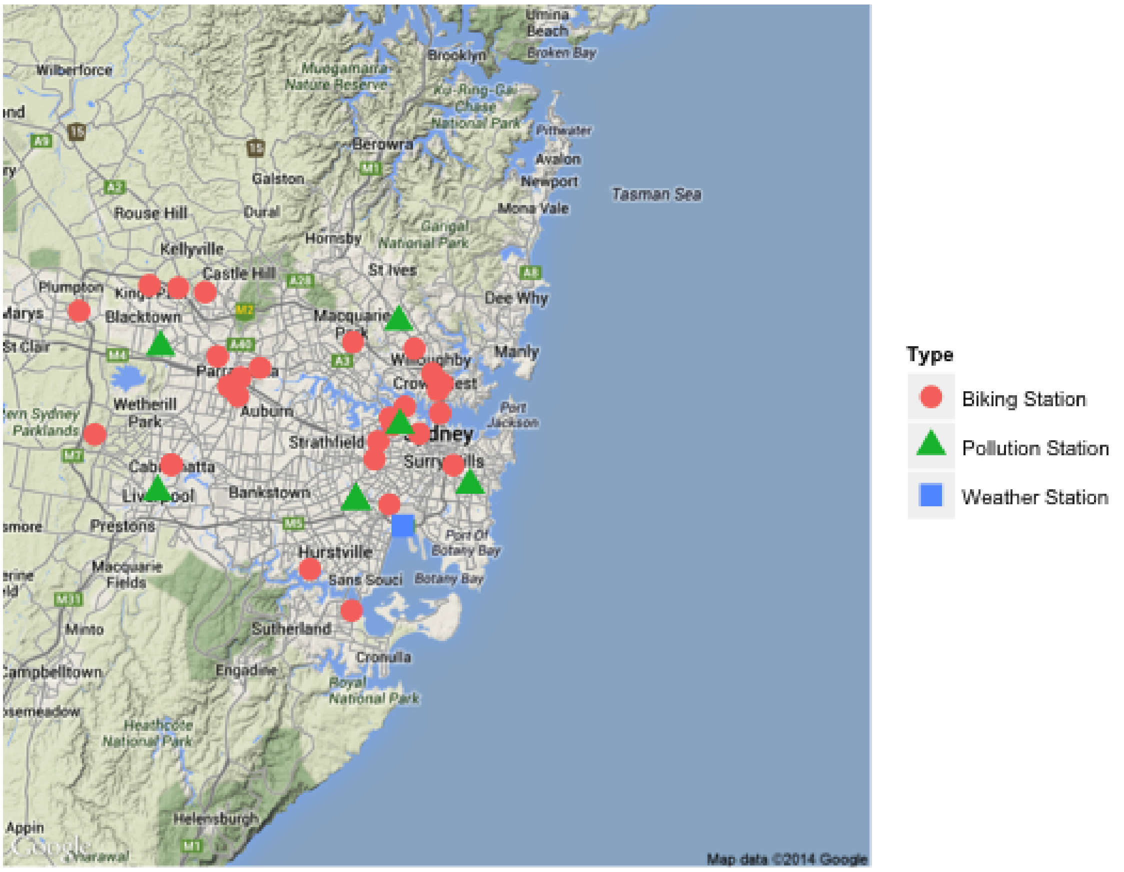
* significant at 5% ** significant at 1% *** significant at 0.1%.

Figure 1: Sydney Regional Cycling Path



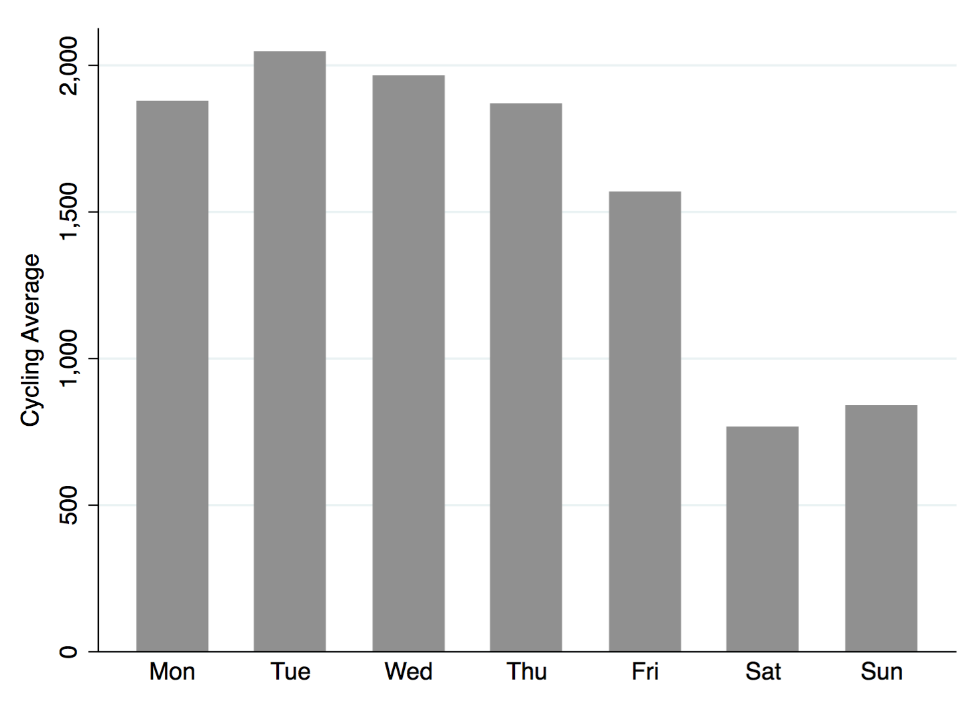
Source: City of Sydney

Figure 2: Cycling, Pollution and Weather, Stations

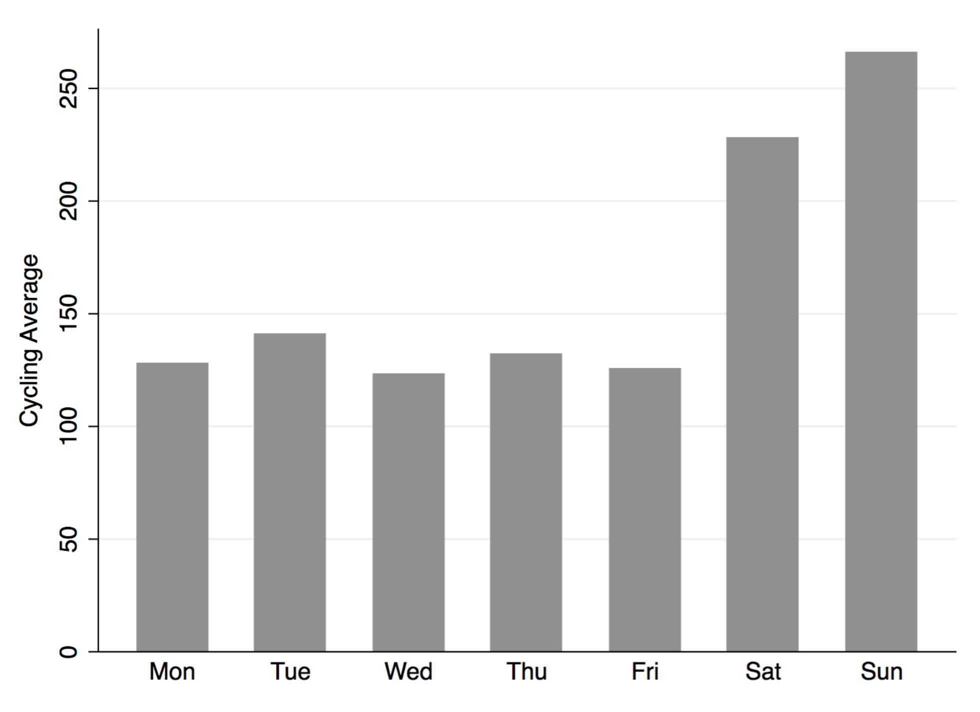


Note: The GPS coordinates of Cycling, Pollution and Weather Station are respectively obtained from the city of Sydney, NSW Office of Environment and Heritage and NSW Bureau of Meteorology. This figure shows all 31 cycling counters while 26 counters are used for our regression.

Figure 3: Average Number of Cyclists Per Day of Week, May 2008 - September 2013.

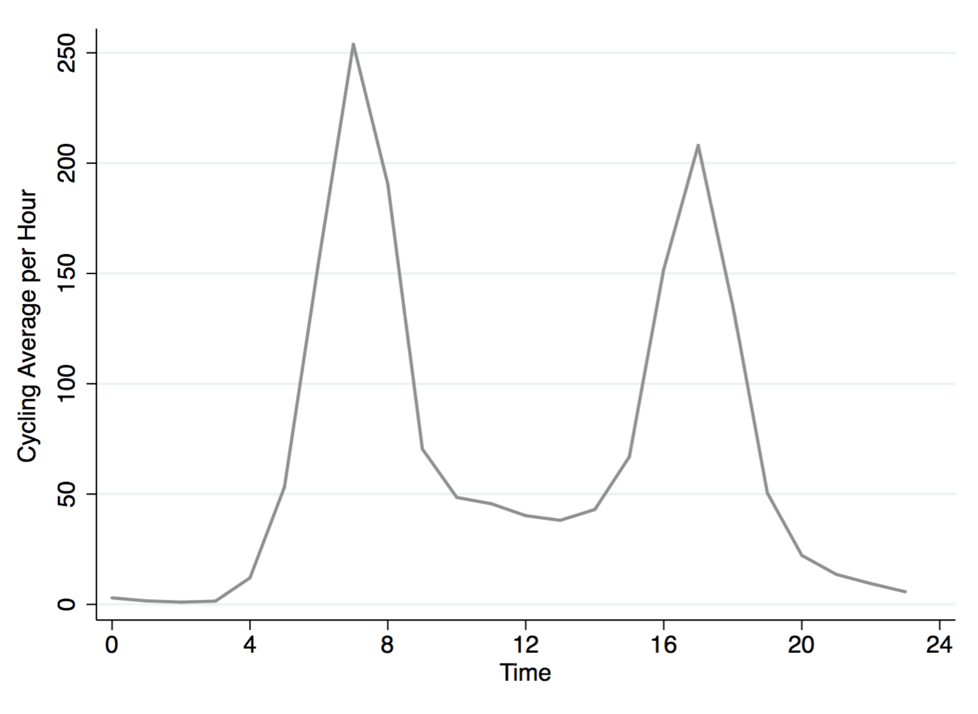


(a) Counter 1 (Harbour Bridge)

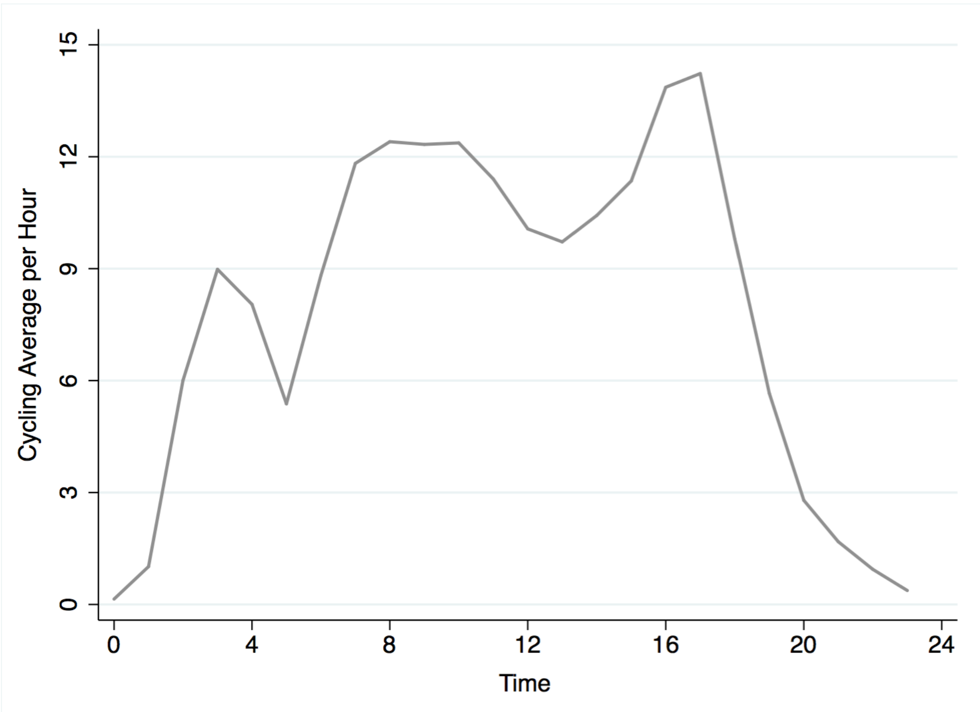


(b) Counter 31 (Como Bridge Cycleway)

Figure 4: Hourly Pattern of Cycling, May 2008 - September 2013.

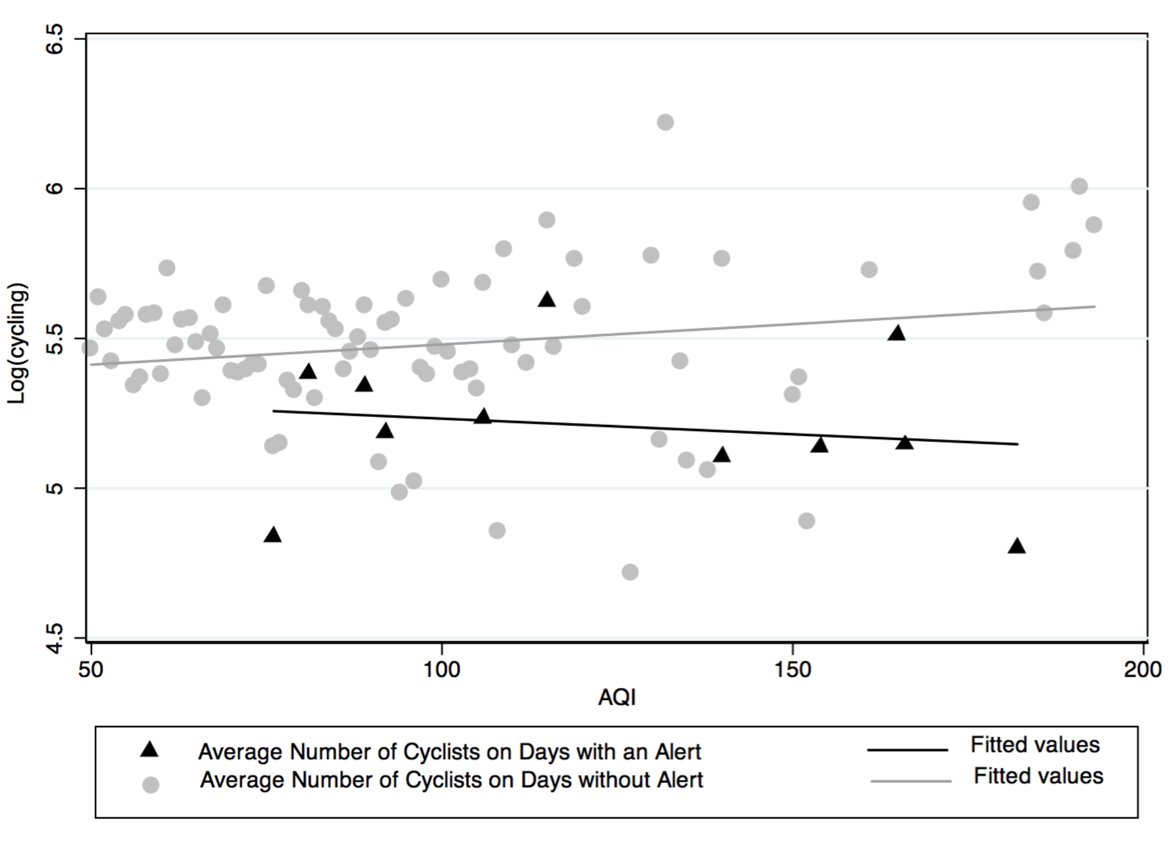


(a) Counter 1 (Harbour Bridge)



(b) Counter 8 (Falcon Street)

Figure 5: Cycling Average On Days With and Without Alerts, No Controls.



Note: Each bin shows the average number of cyclists for the specific observed value of AQI conditional on whether an alert is issued or not. For instance, the black triangle for the AQI=160 shows that the logarithm of average number of cyclists were 5.2 when the observed value of AQI was 160 and an alert was issued.

A Appendix

Table A.1: OLS Regression Results: Full Point Estimates

	(1) Total	(2) Weekdays	(3) Weekends
Alert	-0.141***	-0.162***	-0.265***
	[0.0292]	[0.0422]	[0.0376]
AQI	0.000224	-0.0000380	0.000316
	[0.000114]	[0.000164]	[0.000194]
Max temperature	0.137***	0.108***	0.216***
	[0.00661]	[0.00641]	[0.0120]
Max temperature^2	-0.00252***	-0.00200***	-0.00391***
	[0.000121]	[0.000119]	[0.000238]
Precipitation	-0.0593***	-0.0886***	-0.0432***
	[0.00372]	[0.00511]	[0.00409]
Humidity	-0.00408***	-0.00300***	-0.00600***
	[0.000301]	[0.000331]	[0.000521]
Solar exposure	0.0165***	0.0169***	0.0130***
	[0.00156]	[0.00186]	[0.00211]
Minimum temperature	-0.0148***	-0.00798*	-0.0318***
	[0.00288]	[0.00303]	[0.00355]
Wind Speed	-0.00619***	-0.00558***	-0.00855***
	[0.000667]	[0.000596]	[0.00101]
No of hours of bright sun	0.0172***	0.0182***	0.0178***
	[0.00157]	[0.00171]	[0.00257]
Time Fixed Effect	Y	Y	Y
Cycling Routes Fixed Effect	Y	Y	Y
Observations	28452	20331	8121
R^2	0.261	0.308	0.331

The dependent variable is $log(cycling)$. Clustered by counters, standard errors in brackets. Weather covariates include temperature, maximum temperature, minimum temperature, humidity, solar exposure, wind speed, precipitation and number of hours of bright sun. Pollution covariate includes air quality index. Time dummies include day of week and year-month.

* significant at 5% ** significant at 1% *** significant at 0.1%.

Table A.2: IV Regression Results: Full Point Estimates

	(1)	(2)	(3)
Alert	-0.293***	-0.351***	-0.132**
	[0.0575]	[0.0600]	[0.0476]
AQI	0.00699**	0.00957***	-0.000173
	[0.00227]	[0.00235]	[0.00180]
Max temperature	0.117***	0.109***	0.138***
	[0.00935]	[0.00985]	[0.00800]
Max temperature^2	-0.00241***	-0.00237***	-0.00253***
	[0.000124]	[0.000131]	[0.000113]
Precipitation	-0.0533***	-0.0510***	-0.0597***
	[0.00389]	[0.00392]	[0.00373]
Humidity	-0.00506***	-0.00543***	-0.00403***
	[0.000474]	[0.000500]	[0.000401]
Solar exposure	0.0113***	0.00930***	0.0168***
	[0.00240]	[0.00252]	[0.00197]
Minimum temperature	-0.00724*	-0.00437	-0.0152***
	[0.00301]	[0.00314]	[0.00257]
Wind Speed	-0.00638***	-0.00646***	-0.00618***
	[0.000560]	[0.000580]	[0.000536]
No of hours of bright sun	0.0226***	0.0247***	0.0168***
	[0.00291]	[0.00305]	[0.00249]
Time Fixed Effect	Y	Y	Y
Cycling Routes Fixed Effect	Y	Y	Y
F-Statistic for Excluded Instruments	57.65	33.20	32.17
Observations	28452	28452	28452

The dependent variable is $log(cycling)$. Clustered by counters, standard errors in brackets. Weather covariates include temperature, maximum temperature, minimum temperature, humidity, solar exposure, wind speed, precipitation and number of hours of bright sun. Pollution covariate includes air quality index. Time dummies include day of week and year-month.
* significant at 5% ** significant at 1% *** significant at 0.1%.

Table A.3: Relation Between Cycling and AQI

	(1)
AQI	0.0013***
	[0.00014]
Controls for Weather	N
Control for alert	N
Time Fixed Effect	Y
Cycling Routes Fixed Effect	Y
Observations	28452

Note: This table presents the results of regressing $log(cycling)$ on AQI_t, time and cycling fixed effects. Clustered by counters, standard errors in brackets.
* significant at 5% ** significant at 1% *** significant at 0.1%